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A Framework for Multivariate Process Monitoring and Diagnosis

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Abstract. Monitoring and diagnosis of mean shifts in manufacturing processes become more challenging when involving two or more correlated variables. Unfortunately, most of the existing statistical process control frameworks are only effective in shift detection but suffers high false alarm, that is, imbalanced performance monitoring. The problem becomes more complicated when dealing with small shift particularly in identifying the causable variables. In this research, a framework to address balanced monitoring and accurate diagnosis was investigated. Design considerations involved extensive simulation experiments to select input representation based on raw data and statistical features, recognizer design structure based on synergistic model, and monitoring-diagnosis approach based on two stages technique. The study focuses on correlated process mean shifts for cross correlation function, $\rho = 0.1 \sim 0.9$ and mean shift, $\mu = \pm\, 0.75 \sim 3.00$ standard deviations. The proposed design, that is, an Integrated Multivariate Exponentially Weighted Moving Average with Artificial Neural Network gave superior performance, namely, average run length, $ARL_1 = 3.18 \sim 16.75$ (for out-of-control process), $ARL_0 = 452.13$ (for in-control process) and recognition accuracy, RA = 89.5 ~ 98.5%. This research has provided a new perspective in realizing balanced monitoring and accurate diagnosis of multivariate correlated process mean shifts.

Introduction

In manufacturing industries, process variation has become a major source of poor quality. When manufacturing process involves two or more correlated variables, an appropriate scheme is necessary to monitor these variables jointly. In addressing this issue, the traditional multivariate statistical process control (MSPC) frameworks such as T^2, multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) are known effective in detecting the process mean shifts. Nevertheless, they are lack of capability in identifying the source variables that responsible to the process mean shifts. In other word, it is unable to provide diagnosis information for a quality practitioner towards finding the root cause errors and solution for corrective action. Therefore, major researches have been focused for improving capability in identifying the source variables [1]. In related study, various artificial neural networks (ANN) based frameworks namely, MSPC-ANN [2–5], Novelty Detector ANN [6], Modular-ANN [7], Ensemble-ANN [8] and Multi-Module-Structure-ANN [9] have been investigated for automatically recognizing multivariate process shift patterns. Further discussion on these schemes can be found in reference [10].

In monitoring aspect, these advanced MSPC frameworks have indicated faster shift detection. However, most of them are suffers in high false alarms (average run length, $ARL_0 \leq 200$) in comparison to the *de facto* level for univariate SPC frameworks ($ARL_0 \geq 370$). This would be critical for a quality practitioner in conducting unnecessary troubleshooting due to wrong identification of in-control process as out-of-control. In this study, this situation is called 'imbalanced monitoring'. In diagnosis aspect, on the other hand, they are also lack in accurately identifying the source (causable) variables especially when dealing with small shifts. This would be more difficult for a quality practitioner in searching the root cause errors. In this study, this situation is called 'lack of diagnosis'. In order to overcome these disadvantages, an enhanced framework namely, an integrated MEWMA-ANN was developed towards achieving 'balanced monitoring and accurate diagnosis'. This proposed framework aims for enabling rapid shift detection with minimum false alarm and high accuracy in identifying the source shifted variables. Details discussion is organized as follows. Section 2 presents an enhanced framework. Section 3 then provides performance comparison between an integrated MEWMA-ANN and the baseline ANN frameworks [7, 8]. Section 4 finally outlines some conclusions.

An Enhanced Framework

An integrated MEWMA-ANN framework was designed and developed based on two stages monitoring and diagnosis technique as shown in Figure 1.

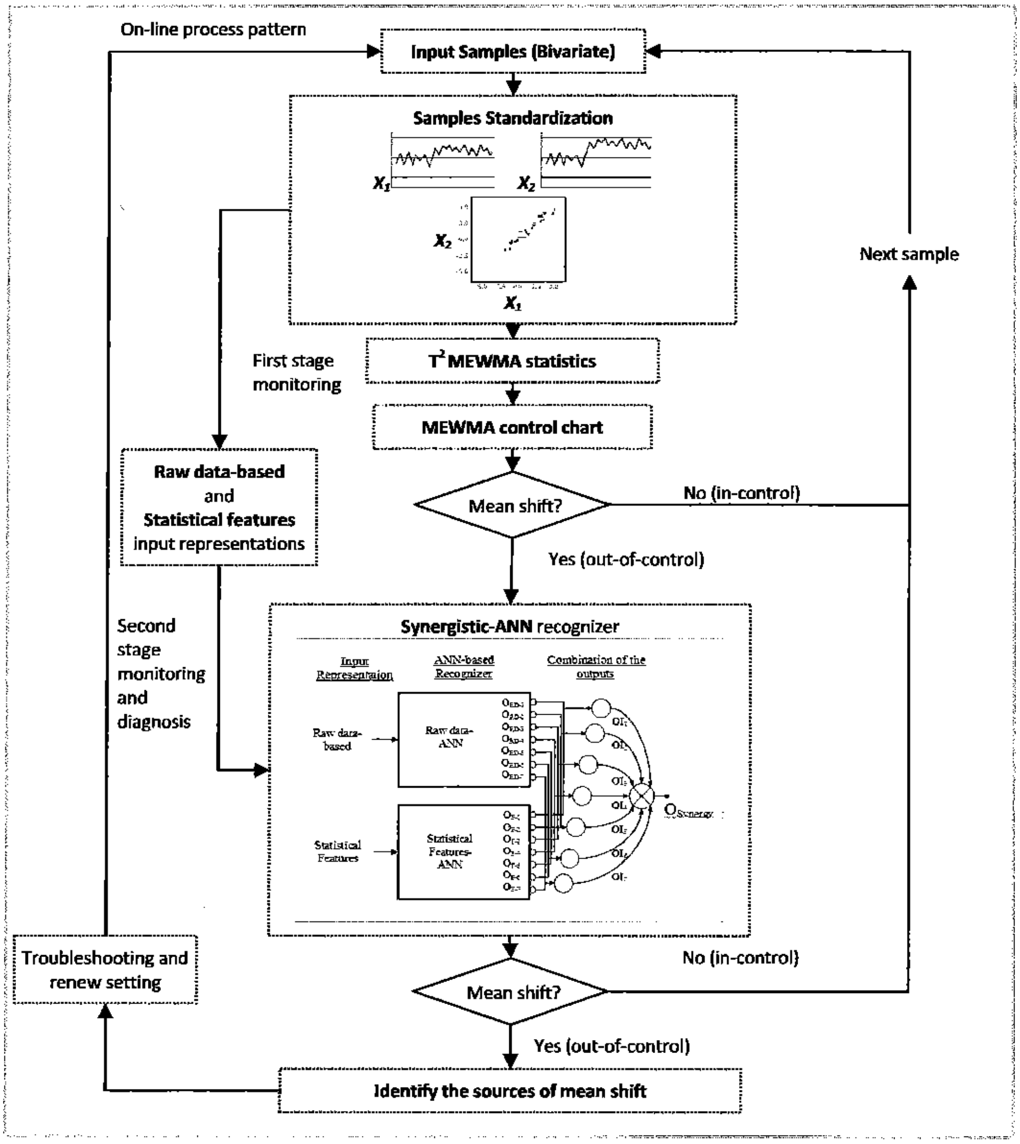

Figure 1. An Integrated MEWMA-ANN framework

Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process in mean shifts. In the first stage monitoring, the MEWMA control chart is utilized for triggering mean shifts in multivariate process based on 'one point out-of-control' procedure. Once the shift is detected, the Synergistic-ANN model is then utilized for conducting second stage monitoring and diagnosis by recognizing data stream pattern contained point(s) out-of-control. Implementation procedures for this proposed framework are summarized in Figure 2. It should be noted that the following initial setting needs to be performed before it can be put into application:

- Load the trained the raw data-ANN recognizer into the system.
- Set the values of means (μ_{01}, μ_{02}) and standard deviations (σ_{01}, σ_{02}) of multivariate in-control process (for variables X_1 and X_2). These parameters can be obtained based on historical samples.
- Perform in-process quality control inspection until 24 observations to begin the system.

Modeling of data patterns of multivariate process mean shifts, and design and training-testing of the synergistic-ANN recognizer can be referred in reference [11]. The formulation of the MEWMA control chart can be found in reference [12]. Parameters (λ, H) = (0.10, 8.64) as reported in reference [13] were selected for this scheme.

Step 1: Input samples (bivariate). Window size = 24, starting observation samples are: $X_{1\text{-}i} = (X_{1\text{-}1}, \ldots, X_{1\text{-}24})$ and $X_{2\text{-}i} = (X_{2\text{-}1}, \ldots, X_{2\text{-}24})$. It is followed by ($i^{th}$ + 1), (i^{th} + 2) and so on.
Step 2: Samples standardization. Rescale observation samples into a standardized range within [−3, +3]: $Z_1 = (X_1 - \mu_{01})/\sigma_{01}$ and $Z_2 = (X_2 - \mu_{02})/\sigma_{02}$
Input samples (original) and standardized samples can be represented graphically using Shewhart control charts and scatter diagram.
Step 3: First stage monitoring (MEWMA control chart):
Standardized samples (Z_1, Z_2) are converted into MEWMA statistics (T^2_{MEWMA}).
Decision rule: *If* T^2_{MEWMA} < Upper control limit (h)
Proceed to the next samples
else
Proceed to the second stage monitoring.
end
Step 4: Input representation.
(i) Raw data-based input representation: $Z_{1\text{-}P1}, Z_{2\text{-}P1}, \ldots, Z_{1\text{-}P24}, Z_{2\text{-}P24}$
(ii) Statistical features input representation:
- Feature extraction: the standardized samples (Z_1, Z_2) are converted into statistical features, namely, the last value of exponentially weighted moving average ($LEWMA_\lambda$) with λ = (0.25, 0.20, 0.15, 0.10), mean (μ), multiplication of mean with standard deviation (MSD), and multiplication of mean with mean square value (MMSV).
- Fourtheen extracted features are represented as follows: ($LEWMA_{0.25\_P1}$, $LEWMA_{0.20\_P1}$, $LEWMA_{0.15\_P1}$, $LEWMA_{0.10\_P1}$, μ_{P1}, MSD_{P1}, $MMSV_{P1}$, $LEWMA_{0.25\_P2}$, $LEWMA_{0.20\_P2}$, $LEWMA_{0.15\_P2}$, $LEWMA_{0.10\_P2}$, μ_{P2}, MSD_{P2}, $MMSV_{P2}$). Number of samples is denoted by P.
Step 5: Second stage monitoring and diagnosis (synergistic-ANN recognizer):
Decision rule: *If* Maximum output of ANN belongs to N(0, 0):
Process is "in-control"; proceed to the next samples
else Process is "out-of-control"; identify the sources of mean shifts; perform diagnosis, troubleshooting; renew setting and return to Step 1 (out of scopes of this research).
end

Figure 2. Implementation Procedure for the Integrated MEWMA-ANN scheme

Performance Results and Discussion

Based on average run lengths (ARL_0, ARL_1) and recognition accuracy percentage (RA) results as summarized in Table 1, the monitoring and diagnosis performances of the proposed framework were evaluated against the baseline frameworks (Modular-ANN [7] and Ensemble-ANN [8]). This is supported mathematically with statistical significant test as summarized in Table 2. The ARL_1 and RA results are taken based on average values regardless the differences in pattern category (sources of variation in mean shift). The proposed framework involves six patterns, Modular-ANN involves eight patterns, whereas Ensemble-ANN involves three patterns. Comparison of ARL_1 and RA results are focused to mean shifts within ± 1.00 ~ 3.00 standard deviations, whereas comparison of ARL_0 is focused on low data correlation (ρ = 0.0 ~ 0.1) since the results for moderate and high data correlations (0.5 ~ 0.9) were not reported in reference [7, 8].

Table 1. Performance comparison between EWMA-ANN and the baseline frameworks

Pattern Category	Mean Shift		Average Run Lengths			Recognition Accuracy		
			Modular-ANN [7]	Ensemble-ANN [8]	MEWMA-ANN	Modular-ANN [7]	Ensemble -ANN [8]	MEWMA-ANN
	X1	X2	ARL_0 for ρ = 0.1, 0.5, 0.9			RA for ρ = 0.1, 0.5, 0.9		
N (0, 0)	0.00	0.00	198	364.82	335.01, 543.93, 477.45	NA	NA	NA
			ARL_1 for ρ = 0.1, 0.5, 0.9					
US (1, 0)	0.75	0.00			17.60, 18.34, 20.00	89.5,		92.7, 90.4, 89.5
US (0, 1)	0.00	0.75	NA	NA	16.20, 15.99, 16.21	91.3,	NA	92.9, 89.3, 90.6
US (1, 1)	0.75	0.75			13.64, 13.28, 14.17			82.4, 94.8, 99.9
DS (1, 0)	−0.75	0.00			16.31, 16.43, 17.35	93.0		92.3, 89.2, 89.4
DS (0, 1)	0.00	−0.75			16.94, 17.44, 18.75			92.3, 87.8, 88.5
DS (1, 1)	−0.75	−0.75			13.46, 13.37, 14.03			84.1, 96.1, 99.9
Average					15.69, 15.81, 16.75			89.5, 91.3, 93.0
US (1, 0)	1.00	0.00		**10.76**	11.52, 11.57, 11.70	**93.3**,		95.3, 93.1, 94.4
US (0, 1)	0.00	1.00			10.50, 10.22, 10.20	94.4,		95.8, 93.5, 94.4
US (1, 1)	1.00	1.00			9.16, 9.09, 9.66			90.0, 96.5, 100
DS (1, 0)	−1.00	0.00			10.99, 10.86, 11.06	95.6		95.3, 93.2, 92.3
DS (0, 1)	0.00	−1.00			11.08, 11.12, 11.36			93.8, 92.1, 92.6
DS (1, 1)	−1.00	−1.00			9.15, 9.12, 9.63			89.5, 98.0, 100
Average					10.40, 10.33, 10.60			93.3, 94.4, 95.6
US (1, 0)	1.50	0.00	3.28,	**6.83**	7.02, 7.07, 7.03	**95.5**,	99.6,	97.4, 96.5, 97.1
US (0, 1)	0.00	1.50	3.39,		6.54, 6.33, 6.40	97.0,	99.1,	97.1, 96.5, 96.2
US (1, 1)	1.50	1.50			5.82, 5.73, 5.94			91.7, 97.9, 100
DS (1, 0)	−1.50	0.00	3.53		6.81, 6.81, 6.92	97.4	88.8	97.4, 96.3, 95.5
DS (0, 1)	0.00	−1.50			6.82, 6.80, 6.85			96.2, 95.8, 95.6
DS (1, 1)	−1.50	−1.50			5.81, 5.69, 5.98			93.2, 99.0, 100
Average					6.47, 6.41, 6.52			95.5, 97.0, 97.4
US (1, 0)	2.00	0.00	2.15,	**5.14**	5.23, 5.15, 5.19	**95.7**,	99.6,	97.8, 97.1, 97.6
US (0, 1)	0.00	2.00	2.35,		4.80, 4.72, 4.70	97.6,	99.7,	97.7, 97.8, 97.1
US (1, 1)	2.00	2.00			4.36, 4.32, 4.39			91.6, 98.4, 100
DS (1, 0)	−2.00	0.00	2.19		5.04, 5.04, 5.02	97.8	94.0	96.8, 96.7, 96.6
DS (0, 1)	0.00	−2.00			4.97, 5.03, 4.98			96.5, 96.5, 95.6
DS (1, 1)	−2.00	−2.00			4.29, 4.27, 4.33			93.7, 98.9, 100
Average					4.78, 4.76, 4.77			95.7, 97.6, 97.8
US (1, 0)	2.50	0.00		**5.74**	4.10, 4.14, 4.12	**96.2**,		98.0, 98.4, 98.0
US (0, 1)	0.00	2.50			3.83, 3.81, 3.81	97.8,		97.3, 97.4, 97.0
US (1, 1)	2.50	2.50			3.54, 3.49, 3.53			93.2, 98.4, 100
DS (1, 0)	−2.50	0.00			3.99, 3.96, 3.95	98.2		97.3, 97.3, 97.0
DS (0, 1)	0.00	−2.50			3.97, 4.02, 3.98			96.5, 96.6, 97.0
DS (1, 1)	−2.50	−2.50			3.41, 3.40, 3.46			94.9, 98.8, 100
Average					3.81, 3.80, 3.81			96.2, 97.8, 98.2
US (1, 0)	3.00	0.00	2.41,	**7.02**	3.47, 3.46, 3.46	**96.6**,	99.3,	98.6, 98.3, 98.2
US (0, 1)	0.00	3.00	2.56,		3.20, 3.20, 3.21	98.0,	99.3,	97.8, 97.8, 98.0
US (1, 1)	3.00	3.00			2.98, 2.93, 2.98			93.8, 98.4, 100
DS (1, 0)	−3.00	0.00	2.47		3.31, 3.30, 3.27	98.5	92.5	98.0, 97.1, 97.6
DS (0, 1)	0.00	−3.00			3.33, 3.32, 3.32			96.7, 97.1, 97.1
DS (1, 1)	−3.00	−3.00			2.84, 2.85, 2.90			94.6, 99.1, 100
Average					3.19, 3.18, 3.19			96.6, 98.0, 98.5
Grand Average	± (0.75 ~ 3.00)				7.39, 7.38, 7.61			94.5, 96.0, 96.8

Note: Design parameters for MEWMA control chart (λ = 0.1, H = 8.64)

Bold values represent the comparison results between EWMA-ANN and Ensemble-ANN frameworks

Table 2. Statistical significant test of performance results in Table 1

Performance Measure (PM)	Result of Paired T-Test and Conclusion					
ARL_1		N	Mean	StDev	SE Mean	Mean difference of ARL_1
	MEWMA-ANN	9	4.808	1.421	0.474	95% CI: (1.277, 2.932)
	Modular-ANN	9	2.703	0.541	0.180	T-Test = 0 (vs ≠ 0): T = 5.860, P = 0.000
	Difference	9	2.104	1.077	0.359	Increment in ARL_1 is proven to be statistically significant.
		N	Mean	StDev	SE Mean	Mean difference of ARL_1
	MEWMA-ANN	5	5.730	2.890	1.292	95% CI: (−3.274, 0.538)
	Ensemble-ANN	5	7.098	2.189	0.979	T-Test = 0 (vs ≠ 0): T = −1.990, P = 0.117
	Difference	5	−1.368	1.535	0.686	Decrement in ARL_1 is not statistically significant.
RA		N	Mean	StDev	SE Mean	Mean difference of RA:
	MEWMA-ANN	9	97.122	1.023	0.341	95% CI: (−3.337, 3.826)
	Modular-ANN	9	96.878	4.064	1.355	T-Test = 0 (vs ≠ 0): T = 0.160, P = 0.879
	Difference	9	0.244	4.659	1.553	Increment in RA is too small (comparable to each other).
		N	Mean	StDev	SE Mean	Mean difference of RA:
	MEWMA-ANN	5	95.460	1.282	0.573	95% CI: (−4.654, 11.374)
	Ensemble-ANN	5	92.100	7.654	3.423	T-Test = 0 (vs ≠ 0): T = 1.160, P = 0.309
	Difference	5	3.360	6.454	2.886	Increment in RA is not statistically significant.

In terms of monitoring aspect, the proposed framework provides longer ARL_0 (335.01) as compared to the Modular-ANN (198). However, this ARL_0 result is quite shorter as compared to the Ensemble-ANN (364.82). On the other hand, it provides longer ARL_0 (543.93, 477. 45) for medium and high data correlations, which is satisfied the desired *de facto* level ($ARL_0 \geq 370$). This means that the proposed framework is capable to maintain minimum false alarm when dealing with medium and highly correlated processes. Based on ARL_1 results, the proposed framework shows better capability in shift detection as compared to the Ensemble-ANN (ARL_1 = 5.73 < 7.098) but less effective as compared to the Modular-ANN (ARL_1 = 4.808 > 2.703).

In terms of diagnosis aspect, the proposed framework gives higher RA in identifying the sources of mean shifts as compared to the Ensemble ANN (overall increment in RA = 3.36 %). Based on comparison against the Modular-ANN, it can be observed that the diagnosis capability of the proposed framework is more effective when dealing with high correlated process but less effective when dealing with low and medium correlated processes.

Conclusions

This paper proposed an integrated MEWMA-ANN scheme towards achieving 'balance monitoring and accurate diagnosis' performances in dealing with bivariate process mean shifts. Based on two-stages monitoring and diagnosis approach, the proposed scheme has resulted in a smaller false alarm, quick mean shift detection and higher diagnosis accuracy compared to the Basic scheme (based on raw data input representation and single ANN recognizer). In the future work, further investigation will be extended to other causable patterns such as trends and cyclic.

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